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PRODUCT DIFFERENTIATION, MULTIPRODUCT FIRMS, AND ESTIMATING THE IMPACT OF TRADE LIBERALIZATION ON PRODUCTIVITY

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This paper studies whether removing barriers to trade induces efficiency gains for producers. Like almost all empirical work which relies on a production function to recover productivity measures, I do not observe physical output at the firm level. Therefore, it is imperative to control for unobserved prices and demand shocks. I develop an empirical model that combines a demand system with a production function to generate estimates of productivity. I rely on my framework to identify the productivity effects from reduced trade protection in the Belgian textile market. This trade liberalization provides me with observed demand shifters that are used to separate out the associated price, scale, and productivity effects. Using a matched plant–product level data set and detailed quota data, I find that correcting for unobserved prices leads to substantially lower productivity gains. More specifically, abolishing all quota protections increases firm-level productivity by only 2 percent as opposed to 8 percent when relying on standard measures of productivity. My results beg for a serious reevaluation of a long list of empirical studies that document productivity responses to major industry shocks and, in particular, to opening up to trade. My findings imply the need to study the impact of changes in the operating environment on productivity together with market power and prices in one integrated framework. The suggested method and identification strategy are quite general and can be applied whenever it is important to distinguish between revenue productivity and physical productivity.

KEYWORDS: Production function, imperfect competition, trade liberalization.

1. INTRODUCTION

OVER THE LAST DECADE, a large body of empirical work has emerged that relies on the estimation of production functions to evaluate the impact of trade policy changes on the efficiency of producers and industries as a whole. There are two main reasons for this development. First, there is a great interest in evaluating policy changes and, more precisely, whether a change in trade policy had any impact on the efficiency of firms in the economy. In this context, being able to estimate a production function using microdata is imperative to recover a *measure* for (firm-level) productivity. Second, the increased availability of international trade data and firm-level data sets for various countries and

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industries has further boosted empirical work analyzing the trade–productivity relationship. A seemingly robust result from this literature is that opening up to trade, measured by either tariff or quota reductions, is associated with *measured productivity gains* and firms engaged in international trade (through export or Foreign Direct Investment (FDI)) have higher measured productivity.²

The *productivity measures* used to come to these conclusions are recovered after estimating a production function where output is replaced by sales, because physical output is usually not observed. The standard solution in the literature has been to deflate firm-level sales by an industrywide producer price index in the hope to eliminate price effects. This has two major implications. First, it will potentially bias the coefficients of the production function if inputs are correlated with the price error, that is, the omitted price variable bias. More precisely, the coefficients of the production function are biased if the price error, which captures the difference between a firm's price and the industry price index, is correlated with the firm's input choices. The use of production function estimation on industries with differentiated products therefore requires controlling for these unobserved prices. Second, relying on deflated sales in the production function will generate productivity estimates that contain price and demand variation.³ This potentially introduces a relationship between *measured productivity* and trade liberalization simply through the liberalization's impact on prices and demand. This implies that the impact on *actual productivity* cannot be identified, which invalidates evaluation of the welfare implications. Given that trade policy is evaluated on the basis of its impact on welfare, the distinction between physical productivity and prices is important.

This paper analyzes the productivity effects of reduced quota protection using detailed production and product-level data for Belgian textile producers.⁴ The trade protection change in my application plays two roles. First, we want to investigate its effects on productivity. Second, it is used to construct a set of plausibly exogenous demand shifters at the firm level. I develop an empirical model to estimate productivity by introducing a demand system in the standard production function framework. While the point that productivity estimates obtained by using revenue data may be poor measures of true efficiency had been made before (Klette and Griliches (1996), Katayama, Lu, and Tybout (2009), Levinsohn and Melitz (2006)), we do not know how important it is in

²Pavcnik (2002) documented productivity gains from trade liberalization in Chile, Javorcik (2004) found positive spillovers from FDI in Lithuania and Van Biesebroeck (2005) found learning by exporting in sub-Saharan African manufacturing. Bartelsman and Doms (2000) and Tybout (2000) reviewed related studies.

³Productivity growth measures are not biased under the assumption that input variation is not correlated with the price deviation when every firm's price relative to the industry producer price index (PPI) does not change over time.

⁴These data have become fairly standard in international trade applications. For instance, similar data are available for India (Goldberg, Khandelwal, Pavcnik, and Topalova (2008)), Colombia (Kugler and Verhoogen (2008)), and the United States.

practice.⁵ My contribution is to empirically quantify the productivity response to a reduction in trade protection while relying on demand shifters and exogenous trade protection measures to control for demand and price effects. My methodology is therefore able to isolate the productivity response to reduced trade protection from the price and demand responses. The suggested method and identification strategy are quite general and can be applied whenever it is important to distinguish between revenue and physical productivity.

Recently the literature has focused almost exclusively on controlling for the simultaneity bias when estimating production functions by relying on proxy methods (Olley and Pakes (1996), Levinsohn and Petrin (2003)). A series of papers used this approach to verify the productivity gains from changes in the operating environment of firms, such as trade liberalization. In almost all of the empirical applications, the omitted price variable bias was ignored or assumed away.⁶ I build on this framework by introducing observed demand shifters, product (-group) controls, and exogenous trade policy changes. This allows me to consider a demand system where elasticities of demand differ by product segment, and to recover estimates for *productivity* and returns to scale.

Using specific functional forms for production and demand, I back out estimates for true productivity and estimate its response to the specific trade liberalization process that took place in the textile market. I find that the estimated productivity gains from relaxing protection are reduced substantially when relying on my empirical methodology. My results further imply that abolishing all quotas would lead to only a 2 percent change in productivity, on average, as opposed to about 8 percent when relying on standard measures of productivity. To my knowledge, this paper is the first to analyze productivity responses to trade liberalization while controlling for price and demand responses, by relying on the insight that changes in quota protection serve as exogenous demand shifters.

The remainder of this paper is organized as follows. In the next section, I introduce the empirical framework of production and demand which generates a revenue generating production function. Before turning to estimation and identification of this model, I provide some essential background information on the trade liberalization process in the textile market and describe the main data sources. This data section highlights the constraints most, if not all, empirical work faces in estimating production functions. Section 4 introduces the specific econometric strategy to estimate and identify the parameters of my model. The main results are presented in Section 5 and I provide various robustness checks in Section 6. I collect some final remarks and implications of my results together with the main conclusion in the final section. The Supplemental Material (De Loecker (2011)) contains Appendixes A–C.

⁵Klette and Griliches (1996) were mostly interested in estimating returns to scale for selected U.S. manufacturing sectors while correcting for imperfect competition in output markets.

⁶Some authors explicitly reinterpreted the productivity measures as sales per input measures. For instance, see footnote 3 of Olley and Pakes (1996, p. 1264).

2. EMPIRICAL MODEL: A FRAMEWORK OF PRODUCTION AND DEMAND

I start out with a model of single product firms to generate the estimating equation of interest. However, given the prevalence of multiproduct and multisegment firms in the data, I discuss the extension toward multiproduct firms. I stress that this extension allows me to use all firms in the data and therefore increase the efficiency of the estimates. The product mix has no role on the production function, but I emphasize the importance of observing the product mix of each firm in my sample to recover segment-specific demand parameters.

2.1. *Single Product Producers*

I consider a standard Cobb–Douglas production function

$$(1) \quad Q_{it} = L_{it}^{\alpha_l} M_{it}^{\alpha_m} K_{it}^{\alpha_k} \exp(\omega_{it} + u_{it}),$$

where a firm i produces a unit of output Q_{it} at time t using labor (L_{it}), intermediate inputs (M_{it}), and capital (K_{it}). In addition to the various inputs, production depends on a firm-specific productivity shock (ω_{it}), which captures a constant term, and u_{it} , which captures measurement error and idiosyncratic shocks to production.

As in most applications, physical output Q_{it} is not observed; therefore, empirical researchers have relied on measures of sales (R_{it}) or value added. The standard solution in the literature has been to deflate firm-level sales by an industrywide producer price index in the hope of eliminating price effects. This has two major implications. First, it potentially biases the coefficients of the production function if inputs are correlated with prices, that is, the omitted price variable bias. Second, it generates productivity estimates that contain price and demand variation. This potentially introduces a relationship between *measured productivity* and trade liberalization simply through the liberalization's impact on prices and demand.

To single out the productivity response to trade liberalization, I introduce a demand system for a firm's i variety in segment s into the production framework. I consider a standard horizontal product differentiation demand system (constant elasticity of substitution (CES)), where I allow for different substitution patterns by segment s :

$$(2) \quad Q_{it} = Q_{st} \left(\frac{P_{it}}{P_{st}} \right)^{\eta_s} \exp(\xi_{it}).$$

This demand system implies that demand for a firm's product depends on its own price (P_{it}), an average price in the industry (P_{st}), an aggregate demand shifter (Q_{st}), and unobserved demand shocks (ξ_{it}). The CES demand system coupled with monopolistic competition implies a constant markup over

marginal cost for every specific segment of the industry of $(\frac{\eta_s}{\eta_s+1})$ or, alternatively, a segment-specific Lerner index $(\frac{1}{|\eta_s|})$. Producers of textiles therefore face different demand elasticities depending on the product segment. My model therefore departs from the single demand parameter model used by Klette and Griliches (1996) and Levinsohn and Melitz (2006), who relied on the number of firms or aggregate industry output to estimate a single markup.⁷ It is worth noting that the aggregate demand shifter Q_{st} represents total demand for textile products (in a given segment) in the market.⁸

As discussed by Klette and Griliches (1996) and Levinsohn and Melitz (2006), I use the demand system (2) to obtain an expression for the price P_{it} . Under the single product case, every firm produces a single variety and, in equilibrium, quantity produced equals quantity demanded. A firm's revenue is simply $R_{it} = Q_{it}P_{it}$, and using the expression for price,

$$(3) \quad R_{it} = Q_{it}^{(\eta_s+1)/\eta_s} Q_{st}^{-1/\eta_s} P_{st}(\exp(\xi_{it}))^{-1/\eta_s}.$$

A final step is to plug the specific production function (1) into equation (3) and consider log deflated revenue ($\tilde{r}_{it} \equiv r_{it} - p_{st}$), where lowercase letters denote logs. This implies the following estimating equation for the sales generating production function:

$$(4) \quad \tilde{r}_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_s q_{st} + \omega_{it}^* + \xi_{it}^* + u_{it}.$$

The coefficients of the production function are reduced form parameters that combine production and demand, and I denote them by β as opposed to the true technology parameters α . The parameters of interest are $\beta_h = (\frac{\eta_s+1}{\eta_s})\alpha_h$ for $h = \{l, m, k\}$, and the segment-specific demand parameters, $\beta_s = \frac{1}{|\eta_s|}$, which are direct estimates of the segment-specific elasticity of demand. Returns to scale in production γ is obtained by summing the production function parameters, that is, $\gamma = \alpha_l + \alpha_m + \alpha_k$. Note that unobserved prices are already picked up through the correlation with inputs and by including the segment-specific output. In Section 4, I discuss the structure of unobserved productivity and demand shocks in detail. For now, I note that both unobservables enter the estimating equation scaled by the relevant demand parameter, just like the production function coefficients, that is, $\omega_{it}^* \equiv \omega_{it}(\frac{\eta_s+1}{\eta_s})$ and $\xi_{it}^* \equiv \xi_{it}|\eta_s|^{-1}$. The difference between both only becomes important when recovering estimates of productivity after estimating the parameters of the model.

⁷These single markup models imply that aggregate technology shocks or factor utilization cannot be controlled for because year dummies can no longer be used if one wants to identify the demand parameter.

⁸I refer to Appendix B for a detailed discussion on the exact construction of this variable in my empirical application. For now, it is sufficient to note that Q_{st} measures total demand for textile products (in segment s) at time t in the relevant market. In my context, it will be important to include imports as well.

2.2. Multiproduct Producers

Anticipating the significant share of multiproduct firms in my data, I explicitly allow for multiproduct firms in my empirical model so as to use the entire sample of firms. However, to use the full data, more structure is required given that standard production data do not record input usage by product. Therefore, to use the product-level information I require an extra step of aggregating the data at the product level to the firm level, where the relevant variables such as sales and inputs are observed. I aggregate the production function to the firm level by assuming identical production functions across products produced, which is a standard assumption in empirical work; see, for instance, Foster, Haltiwanger, and Syverson (2008) and more discussion in Appendix B. Under this assumption, and given that I observe the number of products each firm produces, I can relate the production of a given product j of firm i , Q_{ijt} , to its total input use and the number of products produced. The production function for product j of firm i is given by

$$(5) \quad Q_{ijt} = (c_{ijt}L_{it})^{\alpha_l}(c_{ijt}M_{it})^{\alpha_m}(c_{ijt}K_{it})^{\alpha_k} \exp(\omega_{it} + u_{it})$$

$$(6) \quad = J_{it}^{-\gamma} Q_{it},$$

where c_{ijt} is defined as the share of product j in firm i 's total input use, for instance, labor used on product j at firm i at time t , L_{ijt} , is given by $c_{ijt}L_{it}$. The second line uses the concept that inputs are spread across products in exact proportion to the number of products produced J_{it} such that $c_{ijt} = J_{it}^{-1}$. Introducing multiproduct firms in this framework therefore only requires controlling for the number of products produced, which scales the production from the product level to the firm level. This restriction is imposed to accommodate a common data constraint of not observing input use by product.

I follow the same steps as above by relying on the demand system to generate an expression for firm-level revenue. The demand system is as before, but at the level of a product. The only difference is that to use the equilibrium condition that a firm's total production is equal to its total demand, I have to consider the firm's total revenue over all products it owns $J(i)$, that is, $R_{it} = \sum_{j \in J(i)} P_{ijt} Q_{ijt}$. Combining the production function and the expression for price from (2) leads to an expression for total deflated revenue as a function of inputs, observed demand shifters, productivity, the number of products, and unobserved demand shocks, and is given by

$$(7) \quad \tilde{r}_{it} = \beta_{np} np_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_s q_{st} + \omega_{it}^* + \xi_{it}^* + u_{it},$$

where $np_{it} = \ln(J_{it})$. Refer to Appendix B.3 for an explicit derivation. For a single product firm $\ln(J_{it}) = 0$, whereas for multiproduct firms an additional term is introduced. I can take this last equation to data, except that in addition to firms producing multiple products, they can also be active in different segments. The variation of activity across segments is discussed in the next section.

For single segment firms, it suffices to stack observations across segments, and to cluster the standard errors by segment to obtain consistent estimates and to verify significance levels. Alternatively I can estimate this regression segment by segment, but I can increase efficiency by pooling over all single segment firms, since the production coefficients are assumed not to vary across segments, and simply expand the term on q_{st} to $\sum_s \beta_s s_{is} q_{st}$, where a dummy variable s_{is} is switched on per firm.⁹ This generates estimates for all parameters of interest, including the segment-specific demand parameters from estimating

$$(8) \quad \tilde{r}_{it} = \beta_{np} n p_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \sum_{s=1}^S s_{is} \beta_s q_{st} + \omega_{it}^* + \xi_{it}^* + u_{it}.$$

Going to firms with multiple segments, s_{is} can be anywhere between 0 and 1. In this way, all firms now potentially face S different demand conditions, and the product mix (s_{is}) variance helps to identify the segment demand elasticities.

Estimating the revenue production function across all firms in the data, which consist of single product producers, multiproduct–single segment producers, and multiproduct–segment producers, requires additional restrictions to the underlying production and demand structure. To estimate my model on multiproduct/single segment firms, I rely on proportionality of inputs, which follows the standard in the literature. However, to enlarge the sample to multisegment firms, I need to measure, at the level of a firm, the share of each segment s in the firm's total demand. I consider various approaches to measure the latter and, in addition, I estimate my model on the different sets of firms in the data to verify whether my results are robust to the extra assumptions and potential measurement errors.

Before I discuss the estimation procedure and the identification strategy, I introduce the various data sets I rely on in my empirical analysis. The discussion of the data guides my identification strategy, which requires to control for unobserved demand shocks (ξ_{it}) and productivity shocks (ω_{it}). I control for unobserved productivity shocks by relying on a modification of recently developed proxy estimators initiated by Olley and Pakes (1996) and subsequent work of Levinsohn and Petrin (2003). While segment-specific demand shocks (q_{st}) are directly observed, I rely on detailed product data and firm-specific protection rates to control for unobserved demand shocks which could otherwise bias the production function and demand parameters. I develop an estimation strategy that combines both controls and generates estimates of productivity purged from price variation by jointly estimating production and demand parameters. This approach allows for a separate identification of the productivity and residual demand effect of quota protection.

⁹This assumption is a consequence of not observing inputs broken down by products, a standard restriction in microdata.

3. BACKGROUND ON TEXTILE MARKET AND DATA

I provide some background on the operating environment of Belgian textile producers in the European Union (EU-15) market during my sample period 1994–2002. I show that reduced quota protection had a downward pressure on output prices and led to a reallocation of imports toward low wage textile producers. Furthermore, I describe my three main data sources and highlight the importance of observing a firm's product mix and product-specific protection data.

3.1. *Trade Protection in the Textile Market*

Belgian producers shipped about 85 percent of their total production to the EU-15 market throughout the sample period, or about 8.5 billion Eur. I therefore consider the EU-15 as the relevant market for Belgian producers. This has an important implication for my empirical analysis. I can hereby rely on the drastic change in quota protection that took place in the EU-15 textile market during my sample period to serve two distinct roles in the analysis. First of all, I want to examine its impact on firm-level productivity and the efficiency of the industry. Second, quota protection acts as firm- and time-specific demand shifters which play an important role in the analysis. Given that the protection is decided at the EU level, I treat changes in trade policy as exogenous, as it is hard to argue that a single Belgian producer can impact EU-wide trade policy.

The EU textile industry experienced a dramatic change between 1990 and 2005. Both a significant reduction in quota protection and a reorientation of imports toward low wage countries had an impact on the operating environment of firms. All of this together had an impact on prices, investment, and production in this market. Table I shows the number of quotas and the average quota levels. I describe these data in more detail later in the paper. For now, it suffices to observe the drop in the number of quota restrictions over the sample period. By 2002, the number of quotas had fallen by 54 percent over a 9 year period and these numbers refer to the number of product–supplier restricted imports. The last four columns of Table I present the evolution by unit of measurement and the same pattern emerges: the average quota level for products protected throughout the sample period increased by 72 and 44 percent for products measured in kilograms and number of pieces, respectively. Both the enormous drop in the number of quotas and the increase in the levels of existing quotas point to a period of significant trade liberalization in the EU textile industry. This table does not show the variation in trade protection across products, which is ultimately what determines how an individual firm reacts to such a change. With respect to this dimension, the raw data also suggest considerable variation in the change of quota protection across products. Over the sample period, the unweighted average (across products) drop in the number of supplying countries facing a quota is 36 percent with a standard deviation of 36 percent. For instance, the number of quotas on “track suits of

TABLE I
NUMBER OF QUOTAS AND AVERAGE QUOTA LEVELS (IN MILLIONS)

	Number of Quota Protections	kg		No. of Pieces	
		No. of Quotas	Level	No. of Quotas	Level
1994	1,046	466	3.10	580	8.58
1995	936	452	3.74	484	9.50
1996	824	411	3.70	413	7.95
1997	857	413	3.73	444	9.28
1998	636	329	4.21	307	9.01
1999	642	338	4.25	304	10.53
2000	636	333	4.60	303	9.77
2001	574	298	5.41	276	11.06
2002	486	259	5.33	227	12.37
Change	-54%	-44%	72%	-60%	44%

knitted or crocheted fabric, of wool, of cotton or of man-made textile fibres” dropped by 80 percent, whereas quotas on “women’s or girls’ blouses, shirts and shirt-blouses, whether or not knitted or crocheted, of wool, of cotton or man-made fibres” only dropped by 30 percent. My empirical analysis relies on this product (and time) variation of protection by adding product information to the firm-level production data.

Table II reports the top suppliers of textile products to the EU-15 and their share in total EU-15 imports in 1995 and 2002, as well as the number of quotas they faced. Total imports increased by almost 60 percent from 1995 to 2002 and the composition of supplying countries changed quite a bit. China is responsible for 16 percent of EU imports of textile products by 2002, while only facing about half of the quota restrictions compared to 1995. The Europe Agreements signed with (at the time) EU candidate countries reorientated imports as well. Both Romania and the Czech Republic significantly increased their share in EU imports due to the abolishment of quota protection. Firms operating in this environment clearly faced different demand conditions that in turn are expected to impact optimal price setting.

Finally, when analyzing producer prices of textile products, I find that during 1996–1999 and 2000–2005, prices of textile products remained relatively unchanged and even slightly decreased. Producer prices in the textile sector further diverged from the manufacturing sector as a whole. In fact, in relative terms, Belgian textile producers saw their real prices, compared to the manufacturing sector, drop by almost 15 percent by 2007. This then suggests a potential relationship between producer prices and trade protection. It is important to note that these aggregate prices, PPI, mask the heterogeneity of prices across goods. It is precisely the variation across producers and products that needs to be controlled for, and relying on deflated sales to proxy for output in a production function only corrects for aggregate price shocks. The

TABLE II
TOP SUPPLIERS OF TEXTILE PRODUCTS TO THE EU^a

Country	Top in 1995 (63%)		Country	Top in 2002 (68.3%)	
	Share	No. of Quotas		Share	No. of Quotas
China	10.6	66	China	15.9	35
Turkey	9.4	35	Turkey	12.5	0
India	6.5	19	India	5.6	17
Hong Kong	5.7	32	Romania	5.4	0
Poland	4.2	18	Tunisia	4.4	0
Tunisia	4.1	2	Bangladesh	4.0	3
United States	4.1	0	Morocco	3.8	0
Switzerland	4.0	0	Poland	3.4	0
Morocco	3.8	0	Hong Kong	3.3	18
Indonesia	3.3	14	Indonesia	2.8	12
Pakistan	2.7	15	Pakistan	2.7	14
Bangladesh	2.3	3	Czech Republic	2.3	0
Romania	2.3	30	Republic of Korea	2.2	27
Total imports		45,252			71,414
Imports top 13		28,509			48,776

^aTotal imports are in billions of euros and are from the author's own calculations and EUROSTAT.

product-level quota data highlight the variation of protection across products and suppliers over time, and I will allow prices to vary with changes in protection.

3.2. *Production, Product, and Protection Data*

I rely on detailed plant-level production data in addition to unique information on the product mix of firms and product-specific quota protection data to analyze the productivity effects of decreased quota protection. I describe the three data sets and the main variables of interest in turn.

3.2.1. *Production Data*

My data cover firms active in the Belgian textile industry during the period 1994–2002. The firm-level data are collected from tax records by the National Bank of Belgium and the data base is commercialized by BvD BELFIRST. The data contain the entire balance sheets of all Belgian firms that have to report to the tax authorities. In addition to traditional variables, such as revenue, value added, employment, various capital stock measures, investments, and material inputs, the data set also provides detailed information on firm entry and exit behavior.

Table III reports summary statistics of some of the variables used in the analysis. The last column repeats the finding of a decreased producer price

TABLE III
SUMMARY STATISTICS OF PRODUCTION DATA^a

Year	Employment	Total Sales	VA p/w	Materials	PPI
1994	89	3,185	45.1	13,160	100.00
1995	87	3,562	44.4	14,853	103.40
1996	83	3,418	45.2	14,313	99.48
1997	85	4,290	53.0	16,688	99.17
1998	90	4,482	50.9	17,266	98.86
1999	88	4,248	51.6	15,546	98.77
2000	90	4,763	52.5	17,511	102.98
2001	92	4,984	51.5	17,523	102.67
2002	99	4,500	53.7	17,053	102.89

^aEmployment is average number of full time employees, total sales is given in millions of euros, VA p/w is value added per worker, and materials is given in thousands of euros.

index (PPI) during my sample period. In fact, the organization of employers, FEBELTEX, suggests in their various annual reports that the downward pressure on prices was largely due to increased competition from low wage countries, most notably the Central and Eastern European Countries (CEECs), Turkey, and China. Together with a drop in the average price, the industry as a whole experienced a downward trend in sales at the end of the nineties, as shown in the third column. Average value added per worker, often used as a crude measure of productivity, increased by 19 percent. The raw data clearly indicate a positive correlation between decreased quota protection and productivity, on the one hand, and a downward pressure on prices, on the other hand. This paper provides an empirical model to quantify both effects, and to isolate the productivity response from the price and demand effects.

3.2.2. Product-Level Data

The employer's organization of the Belgian textile industry (FEBELTEX (2003)) reports product-level information for around 310 Belgian textile producers.¹⁰ More precisely, they list all products produced by every textile producer, and the products are classified into five segments and various subsegments based on the relevant markets of the products. From this, I constructed the product mix of each firm: Table A.I lists the five segments of the textile market with their corresponding product categories. I matched the product information with the production data set (BELFIRST) and ended up with 308 firms for which I observe both firm-level and product-level information. After matching both data, I cover about 75 percent of total employment in the textile industry.

¹⁰The firms listed in FEBELTEX account for more than 85 percent of value added and employment, and the data were downloaded online (www.febeltex.be) during 2003–2004.

TABLE IV
NUMBER OF FIRMS ACROSS DIFFERENT SEGMENTS^a

	Interior	Clothing	Technical	Finishing	Spinning
Interior	<i>77.0</i>	4.8	15.8	7.3	1.8
Clothing		<i>58.9</i>	33.9	7.1	1.8
Technical			<i>35.1</i>	19.6	17.5
Finishing				<i>39.6</i>	12.5
Spinning					<i>47.5</i>
No. of firms	165	56	97	48	40

^aCells do not sum to 100 percent by row or column, as a firm can be active in more than two segments.

For each firm, I observe the number of products produced, which products, and in which segment(s) the firm is active. There are five segments: (i) Interior, (ii) Clothing, (iii) Technical Textiles, (iv) Finishing, and (v) Spinning and Preparing (see Appendix A for more on the data). In total there are 563 different products: on average, a firm produces nine products and 50 percent of firms have three or fewer products. Furthermore, around 25 percent of firms are active in more than one segment and they are, on average, 20 percent larger in terms of sales and employment.

This information is in itself interesting and relates to recent work by Bernard, Redding, and Schott (2010), who looked at the importance of differences in product mix across firms and time, where they relied on a 5 digit industry code to define a product. Given that I rely on a less aggregated definition of a *product*, it is not surprising that I find a higher average number of products per firm.

Table IV presents a matrix where each cell denotes the percentage of firms that are active in both segments. For instance, 4.8 percent of firms are active in both the Interior and Clothing segments. The high percentages in the diagonal (set in *Italic* type) reflect that most firms specialize in one segment; however, firms active in the Technical and Finishing segments tend to be less specialized, as they capture applying and supplying segments, respectively.

The same exercise can be done based on the number of products and is shown in Table V. The concentration of activities into one segment is even more pronounced when relying on the product-level data. The number in each cell denotes the average (across firms) share of a firm's products in a given segment relative to its total number of products. The table has to be interpreted in the following way: firms that are active in the interior segment have (on average) 83.72 percent of all their products in the Interior segment. The analysis based on the product information reveals that some firms concentrate their activity in one segment, while others combine different product segments. Firms active in any of the segments tend to have quite a large fraction of their products in Technical textiles, between 8.27 and 27.7 percent. Finally the last two

TABLE V
FIRMS' PRODUCT MIX ACROSS DIFFERENT SEGMENTS

	Interior	Clothing	Technical	Finishing	Spinning
Interior	83.72	2.78	8.27	4.41	0.80
Clothing	3.03	79.28	15.36	1.86	0.48
Technical	7.01	8.97	70.16	9.06	4.79
Finishing	5.75	3.52	15.53	72.85	2.35
Spinning	3.72	0.65	27.20	7.40	61.04
Median	2	6	8	11	9
Min	1	2	1	2	1

rows of Table V show the median and minimum number of products owned by a firm across the different segments. Firms that produce only two (or less) products are present in all five segments, but the median varies somewhat across segments.

3.2.3. Protection Data

The quota data come directly from the *Système Integre de Gestion de Licenses (SIGL)* data base constructed by the European Commission and is publicly available online (see Appendix A). This data base began in 1993 and reports all products that hold a quota at some point in time for a given supplying country. For each product, the following data are available: the supplying country, product, year, quota level, working level, licensed quantity, and quantity actually used by the supplying country.¹¹ From this I constructed a data base that lists product–country–year specific information on quotas relevant to the EU market. In total there are 182 product categories and 56 supplying countries, where at least one quota on a product from a supplier country in a given year applies. As discussed before, Table I presents the change in protection in the raw data and highlights the sharp drop in the number of quota protections as well as the increase in average quota levels.¹²

I create a composite variable that measures the extent to which a firm is protected (across its products). A first and most straightforward measure is a dummy variable that is 1 if a quota protection applies for a certain product category c on imports from country e in year t (qr_{ect}) and switches to 0 when

¹¹Appendix A.4 describes the quota data in more detail and provides two cases of how quota protection changed.

¹²For the remainder of this paper, I work under the assumption that no remaining tariffs are in place after quotas are abolished. The quotas in my model therefore impact residual demand, after which no more protection occurs. This working assumption is consistent with EU trade policy in the textile market where the bulk of imported goods are exempt from tariffs and where quotas are the predominant trade policy tool.

the quota no longer applies. The average quota restriction that applies to a given product c is given by

$$(9) \quad qr_{ct} = \sum_e a_{et} qr_{ect},$$

where a_{et} is the weight of supplier e in period t .¹³ I experiment with various weights for a_{et} , ranging from gross domestic product (GDP) shares, total output in textile products, export shares of a given supplier e , and simple averages. It is important to stress that my weights take into account the production potential of each supplier and are not related to the actual size of the quota. More specifically, I construct a_{et} as the share of a country e 's production (of textile products) in total production across all supplying countries. When a quota is abolished for a very small country, that is, with a small production potential, a_{et} is very close to zero and therefore its impact on my (firm-level) liberalization variable is extremely small. This measure, qr_{ct} , is 0 if not a single quota applies to imports of product c from any of the supplying countries at a given time and is 1 if it holds for all supplying countries.

A final step is to relate the quota restriction measure to the firm-level data.¹⁴ I aggregate the product-level quota measure qr_{ct} to the level of a firm i using the product mix information and recover a firm-specific quota protection measure (qr_{it}). More precisely, I take a weighted sum over all products c that a firm produces, $c \in J(i)$, to obtain

$$(10) \quad qr_{it} = \sum_{c \in J(i)} a_c qr_{ct},$$

where a_c represents the share of product c in a firm's production so as to weigh the protection across products accordingly. Because of differences in product classification of the quota data and the production data, I can only rely on simple averages to compute qr_{it} by considering the average of qr_{ct} across a firm's products.

The protection rate variable (qr_{it}) lies between 0 and 1: it is 0 if not a single product is protected and is 1 if all its products are protected from all supplying countries. Figure 1 shows the evolution of the quota restriction variable given

¹³As noted by a referee, a more general treatment would allow for a product–supplier weight a_{ect} . However, due to data restrictions, I consider a constant share across product categories within a supplier–year. To be able to compute a more general share which is product–supplier specific, I need to observe production at the product level for all 52 supplying countries and these data are very hard to come by.

¹⁴The 182 different quota product categories map into 390 different 8 digit product codes. The latter correspond to 23 different 4 digit industry classifications (equivalent to the 5 digit standard industrial criterion (SIC) level in the U.S.) that allow me to relate the quota restriction variable to the firm-level variables.

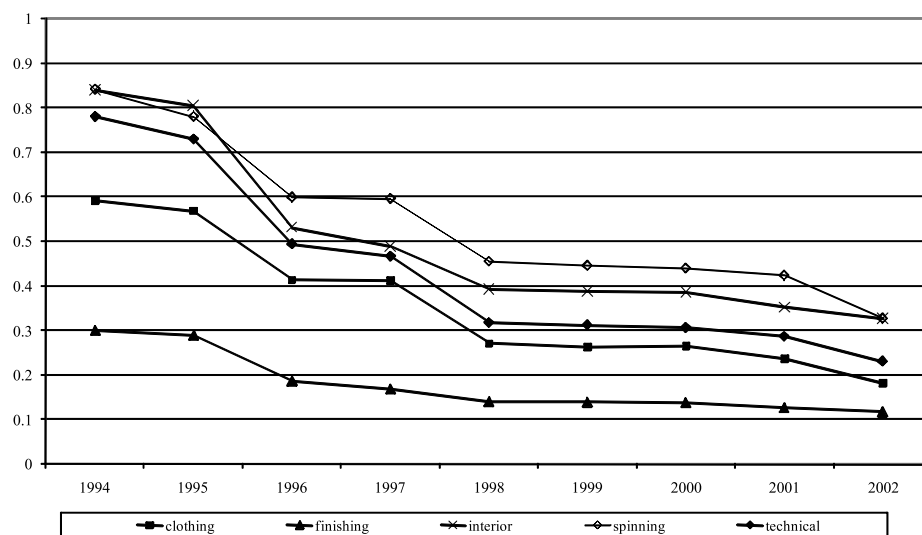


FIGURE 1.—Evolution of quota restriction measure by segment (1994–2002).

by (10) for each segment. In all segments the average quota restriction has gone down considerably over the sample period. However, there is significant variation across segments which will be important to identify segment-specific demand elasticities.

Quota levels are not reflected in my measure of trade liberalization. However, I relate changes in quota levels to firm-level productivity in the empirical analysis. The latter picks up changes in protection intensity, conditional on having a quota in place.¹⁵ In the next section, I discuss my empirical strategy to deal with unobserved productivity and demand shocks. The estimation procedure relies on observing demand shifters, such as the protection rate variable qr_{it} , so as to jointly estimate demand and production parameters.

4. ESTIMATION AND IDENTIFICATION

In this section, I describe the estimation procedure to obtain estimates of the production function and demand parameters, which are needed to obtain estimates for productivity. Finally, I discuss some remaining identification issues.

¹⁵In principle, I could use my method to construct an alternative measure of protection where I rely on the quota levels and weigh them by production potential. The problem lies now in aggregating quota levels measured in various units (kg, m³, etc.). I therefore choose to rely on a cleaner measure, that is, a quota dummy, to construct a measure for protection.

4.1. Estimation Strategy

I lay out the estimation procedure that provides me with estimates of the production function coefficients and the demand parameters. The estimating equation for single product firms is given by

$$(11) \quad \tilde{r}_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_s q_{st} + \omega_{it}^* + \xi_{it}^* + u_{it},$$

where the ultimate goal is to recover estimates of productivity. Note that the asterisks on the unobservables only keep track of the difference between the actual productivity (demand) unobservable and that unobservable multiplied by the inverse demand parameter, as discussed in Section 2. To obtain consistent estimates of the revenue production function, I need to control for both unobserved productivity shocks and unobserved demand shocks.

Both the estimation procedure and the identification strategy are identical for the multiproduct and multisegment producers where an additional term, $\beta_{np} np_i$, enters the estimating equation. This has no implications on the ability to identify the parameters of interest, as the product mix is assumed to be fixed over time. When estimating this equation over multisegment firms, I consider the same expansion of the output variable as before, $\sum_s \beta_s s_{is} q_{st}$, to account for the different demand conditions across segments: Appendix B.3 provides more details.

As noted before, under the CES demand structure, unobserved prices are picked up by the variation in inputs and by aggregate demand (q_{st}). However, other factors that impact firm-level prices and that are unaccounted for will potentially bias the coefficients of interest. In my setting a likely candidate is quota protection. Differences in protection across producers and over time are expected to impact firm-level residual demand and hence prices. I follow Goldberg (1995) and decompose the unobserved demand shock ξ_{it} based on the nesting structure of the product data into three observable components and an unobserved firm-specific demand shock. The observed components are based on the firm-specific protection rate, the products a firm produces, and the subsegment of the industry in which the firm is active (Table A.II). Formally, let ξ_{it} be decomposed into the components

$$(12) \quad \xi_{it} = \xi_j + \xi_g + \tau q r_{it} + \tilde{\xi}_{it},$$

where j refers to a product, g refers to a product group (subsegment), and τ is a coefficient.¹⁶ In this way I capture persistent product-group differences in demand as well as differences in protection. It will be important to keep track of the properties of the protection variable, $q r_{it}$, for the specific estimation procedure. As discussed in Section 3, the protection differs by product, and because

¹⁶The demand unobservable ξ_{it}^* is again simply related to ξ_{it} via a common parameter and does not affect the results. All coefficients on the product, product-group, and protection capture the relevant segment Lerner index $|\eta_s|^{-1}$.

firms have different product mixes, the protection rate varies across firms and acts as a firm-specific residual demand shock. I assume that the remaining demand shocks ($\tilde{\xi}_{it}$) are independent and identically distributed (i.i.d.) across producers and time.

In terms of the data, j is a product within a subsegment g which belongs to a given segment s . To illustrate the various components of ξ_{it} , I present the detailed structure for the Mobiltech sub-segment within the technical segment in Table A.II. This implies that, in this example, I control for differences in demand (and thus prices) across the nine subsegments (g) of the technical segment and within each subsegment for differences across the products, in addition to (potential) differences in protection rates.

This leads to the main estimating equation of interest

$$(13) \quad \tilde{r}_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_s q_{st} \\ + \sum_{j \in J(i)} \delta_j D_{ij} + \sum_{g \in G(i)} \delta_g D_{ig} + \tau q r_{it} + \omega_{it}^* + \varepsilon_{it},$$

where $J(i)$ and $G(i)$ denote the set of products and product groups a firm markets, respectively. The variables D_{ij} and D_{ig} are dummy variables that take on value 1 if a firm i produces a product (product group) j (g) and are 0 otherwise. In what follows, I collect all product and product-group dummies in $\delta D = \sum_{j \in J(i)} \delta_j D_{ij} + \sum_{g \in G(i)} \delta_g D_{ig}$. Finally, ε_{it} captures idiosyncratic shocks to production (u_{it}) and demand ($\tilde{\xi}_{it}$).

The product and group effects enter my model to control for unobserved demand shocks, and given my assumption on the production function, they should not reflect any difference in technology across products. However, if this assumption fails, the product and group effects might capture technology differences across producers of different products and product groups. This distinction becomes unimportant when I evaluate the productivity-protection relationship, because time invariant factors are eliminated as I am interested in relating protection to productivity changes. I revisit this when I discuss my productivity estimates.

To estimate the parameters of the production function and the demand system, I rely on the insight of Olley and Pakes (1996) and Levinsohn and Petrin (2003) to proxy for unobserved productivity. I present both approaches in the context of my setting and provide conditions under which the parameters of interest are identified. The exact underlying assumptions depend on whether I rely on a static input (e.g., materials) or a dynamic control (investment) to proxy for productivity.

The empirical literature has been vague about how trade shocks enter the productivity process. Given the research question at hand, it is clear that allowing for reduced quota protection to impact (firm-level) demand is desirable, and here I allow quotas to impact firm-level residual demand instantaneously

and therefore to impact equilibrium prices. However, the mechanism through which quotas impact productivity is less obvious. Standard approaches implicitly rely on a story of X-inefficiency: firms can react to increased competition by eliminating inefficiencies, whereas aggregate productivity increases can come about by reallocation and exit. In my case, plant managers who face less quota protection could cut slack, which might reflect in higher productivity. This does not capture productivity changes due to active investment decisions based on expectations of future product market toughness, which allow quota protection to causally impact future productivity.

I consider a process whereby lagged quota protection is allowed to impact productivity and thereby affect productivity changes as

$$(14) \quad \omega_{it} = g_t(\omega_{it-1}, qr_{it-1}) + v_{it}.$$

The law of motion on productivity highlights the two distinct effects of quotas. Firm-level productivity can only react to quota protection with a lag. The latter captures the idea that it takes time for firms to reorganize, cut slack, hire a new manager, or introduce better production–supply management without affecting input use, which can all lead to a higher ω_{it} . On the other hand, quotas can impact residual demand (and prices) instantaneously and create variation in firm-level revenue.

As discussed in the [Introduction](#), I work under the assumption that an individual producer has no power over setting quotas, and this exogeneity of quota is important for my identification strategy, as the shocks to productivity, v_{it} , are not correlated with current quota levels qr_{it} and, by construction, are not correlated with lagged quota qr_{it-1} .

After describing the estimation procedures, I briefly discuss the identification of the variable and static inputs (labor and intermediate inputs) in both approaches given the recent state of the literature. I evaluate the different assumptions in my application and test them where possible. It is important to note that my approach does not require a specific proxy estimator. In fact, the discussion below should help subsequent empirical work trade off these various assumptions.

4.1.1. *Using a Static Input*

The main advantages of relying on the insight of Levinsohn and Petrin (2003; LP hereafter) in my setting are twofold. First of all, I do not have to revisit the underlying dynamic problem of the firm; put differently, I do not have to take a stand on the exact role and process of the protection variable qr_{it} that enters as a residual demand shock and potentially impacts productivity. The use of a static input does not require me to model additional serially correlated variables (state variables); it simply exploits the static input demand conditions. Second, I can rely on intermediate inputs as opposed to investment data for which all firms report positive values at each point in time.

The starting point is to observe that the choice of materials m_{it} is directly related to a firm's productivity level, capital stock, and all demand variables (qr_{it} , q_{st} , D), including quota protection, segment demand and product-group dummies which impact a firm's residual demand and hence determine optimal input demand. This gives rise to the material demand equation

$$(15) \quad m_{it} = m_t(k_{it}, \omega_{it}, qr_{it}, q_{st}, D).$$

Before proceeding, I have to verify whether input demand is monotonically increasing in productivity under imperfect competition. In Appendix C.1, I show that monotonicity is preserved under the monopolistic competition setup with constant markups. This finding is intuitive, as under the constant markup assumption, markups are not related to productivity. I rely on a function $h_t(\cdot)$ to proxy for productivity:

$$(16) \quad \omega_{it} = h_t(k_{it}, m_{it}, qr_{it}, q_{st}, D).$$

The estimation procedure consists of two stages as in the standard LP case, except for the fact that I obtain both demand and supply parameters. I will highlight the differences with respect to the original LP framework, and refer to Levinsohn and Petrin (2003) for more details. The first stage consists of the partial linear model

$$(17) \quad \tilde{r}_{it} = \beta_l l_{it} + \phi_t(m_{it}, k_{it}, qr_{it}, q_{st}, D) + \varepsilon_{it},$$

where $\phi_t(\cdot) = \beta_m m_{it} + \beta_k k_{it} + \beta_s q_{st} + \delta D + \tau qr_{it} + h_t(\cdot)$.¹⁷ The first stage could then, in principle, identify the labor coefficient. I discuss the identification of the labor coefficient in the first stage in a separate section. For now I want to focus on the correction of price variation when estimating the production function.

The second stage provides the moments to identify the parameters of interest after constructing the innovation in the productivity process. Relying on the productivity process (14), where past quota can impact current productivity, I can obtain the innovation in productivity $v_{it+1}(\beta_m, \beta_k, \beta_s, \tau, \delta)$ as a residual by nonparametrically regressing $\omega_{it+1}(\beta_m, \beta_k, \beta_s, \tau, \delta)$ on $\omega_{it}(\beta_m, \beta_k, \beta_s, \tau, \delta)$ and qr_{it} , and we know productivity from the first stage for given values of the parameters

$$\begin{aligned} \omega_{it+1}(\beta_m, \beta_k, \beta_s, \tau, \delta) &= \hat{\phi}_{it+1} - \beta_m m_{it+1} - \beta_k k_{it+1} \\ &\quad - \beta_s q_{st+1} - \tau qr_{it+1} - \delta D. \end{aligned}$$

¹⁷The control function $\phi_t(\cdot)$ always contains the demand parameter as well, and reflects the difference between the structural error ω_{it} and how it enters the main estimating equation ω_{it}^* .

The parameters are obtained by generalized method of moments (GMM) using the moment conditions

$$(18) \quad E \left\{ v_{it+1}(\beta_m, \beta_k, \beta_s, \tau, \delta) \begin{pmatrix} m_{it} \\ k_{it+1} \\ q_{st} \\ qr_{it+1} \\ D \end{pmatrix} \right\} = 0.$$

More precisely, the demand parameter τ is identified by the moment $E(qr_{it+1}v_{it+1}) = 0$ by relying on the exogeneity of quotas as motivated in the [Introduction](#) of this paper. The demand parameter β_s is identified by the condition that shocks to productivity are not correlated with lagged total (segment) output.¹⁸ The coefficients on material and capital are identified using the standard moment conditions in the literature.

For the practical implementation, I do not consider interaction terms between the product dummies D and the other variables. However, the first stage coefficients of these product dummies contain both the demand parameters and the inverse productivity parameters. Therefore, I cannot simply use the first stage estimates to subtract out these product effects. Instead I obtain an estimate of productivity that contains the product effects and control for product-group effects when constructing the innovation in productivity, v_{it+1} by including D in the nonparametric regression of ω_{it+1} on ω_{it} and qr_{it} . This implies that I do not obtain estimates of δ , which are not of direct interest but serve to control for product-specific demand controls. The sample analogue of (18), given by

$$(19) \quad \frac{1}{N} \frac{1}{T} \sum_i \sum_t v_{it+1}(\beta_m, \beta_k, \beta_s, \tau, \delta) \begin{pmatrix} m_{it} \\ k_{it+1} \\ q_{st} \\ qr_{it+1} \\ D \end{pmatrix},$$

is minimized using standard GMM techniques to obtain estimates of the production and demand parameters. The above procedure generates a separate estimate of the quota's effect on productivity (through $g(\cdot)$) and on demand (τ). The intuition behind this result comes from the fact that in my model, protection can only affect productivity with a lag, while current quota protection can impact prices through residual demand.

¹⁸In principle, I could rely on q_{st+1} as well, but this would depend on there being no correlation between total output produced in a segment and shocks to productivity, which is clearly a stronger assumption. In particular, since total output is a weighted sum of producer-level output, the correlation between the latter and productivity shocks is the reason why we need to control for unobserved productivity shocks when estimating production functions in the first place. We would, therefore, require the correlation to get washed out in the aggregate, which is not likely.

4.1.2. Using a Dynamic Control

The Olley and Pakes (1996; hereafter OP) model relies crucially on the notion that the investment policy function $i_t(\cdot)$ can be inverted to proxy unobserved productivity by a function of investment and capital. However, as mentioned in LP, given that my problem is not the standard OP model, I have to verify whether invertibility is preserved with the introduction of quotas into the model. That is, if quotas are correlated over time and not simply i.i.d. shocks, the quota variable qr_{it} will constitute a new state variable in the dynamic problem of the firm. The investment equation in my setting is

$$(20) \quad i_{it} = i_t(k_{it}, \omega_{it}, qr_{it}, D),$$

where the product-group dummies need to be included as well. The data suggest that the segment output variable q_{st} is not serially correlated conditional on qr_{it} and D ; therefore, I do not treat it as a state variable.¹⁹ To invert the investment equation, I need to restrict the role of quotas in the model. The proof by Pakes (1994) goes through under the assumption that qr_{it} is an exogenous state variable with known support: here it lies between 0 and 1. This implies that the level of protection at time t provides a sufficient statistic for future values of quotas. Although restrictive, it does get at an important mechanism through which differences in quotas across firms (through products) lead to differences in investment. Note that this rules out differences in beliefs about future quotas for firms with identical quotas at time t . I discuss this restriction and report a robustness check in Appendix C.2. Inverting equation (20) generates the basis for estimation, since I can use

$$(21) \quad \omega_{it} = h_t(k_{it}, i_{it}, qr_{it}, D)$$

to proxy for unobserved productivity. It is important to highlight that quotas enter through shocks to residual demand and through the investment equation. If $\tau = 0$ and quotas do not impact residual demand, quota protection still enters the investment proxy because quota, potentially, impact the law of motion for productivity.

The first stage is then given by

$$(22) \quad \tilde{r}_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_s q_{st} + \phi_t(i_{it}, k_{it}, qr_{it}, D) + \varepsilon_{it},$$

where $\phi_t(\cdot) = \beta_k k_{it} + \tau qr_{it} + \delta D + h_t(i_{it}, k_{it}, qr_{it}, D)$. This first stage identifies the coefficients on labor, intermediate inputs, and the demand elasticity. I revisit the identification of the variable static inputs (β_l and β_m) below.

¹⁹I can easily accommodate q_{st} being serially correlated over time by including it in the investment equation and identifying its coefficient in the final stage by considering the moment $E(v_{it+1}q_{st}) = 0$, just as in the material demand approach discussed before.

The second stage rests on the estimated parameters of the first stage and identifies the remaining production and demand parameters in a similar way as the static input model discussed before. More precisely, I consider the moments

$$(23) \quad E \left\{ v_{it+1}(\beta_k, \tau, \delta) \begin{pmatrix} k_{it+1} \\ qr_{it+1} \\ D \end{pmatrix} \right\} = 0.$$

Productivity is known up to parameters, $\omega_{it}(\beta_k, \tau, \delta) = \hat{\phi}_{it} - \beta_k k_{it} - \tau qr_{it} - \delta D$, and given the law of motion on productivity, I can recover the residual $v_{it+1}(\beta_k, \tau, \delta)$ by nonparametrically regressing $\omega_{it+1}(\beta_k, \tau, \delta)$ on $\omega_{it}(\beta_k, \tau, \delta)$ and qr_{it} . As in the material demand approach, I assume for computational convenience, that the product effects do not interact with the other state variables and, therefore, I do not have to search over all product dummy coefficients together with the coefficients of interest.

The only difference with the static input version is that productivity shocks are controlled for by variation in investment choices rather than by variation in material demand choices. However, my setting also echoes the argument made by Levinsohn and Petrin (2003) on the advantage of using a static input to control for productivity by avoiding the extra complexity of relying on a dynamic control. In my setting, I need to specify the role of protection and incorporate an additional state variable in the underlying framework of Olley and Pakes (1996): Appendix C.2 discusses this complication further. However, I show that my framework can accommodate both approaches, and recover estimates of productivity and the productivity effect of quota reduction in this setup, which is the ultimate goal of this paper.

4.2. Identifying Variable Inputs' Coefficients

There has been some recent discussion on the ability to identify the variable input coefficients—labor and material inputs in my case—in the first stage of OP and LP. I briefly present how I can accommodate these concerns in my approach either by estimating the coefficient of labor (and materials under the OP approach) in a second stage or by following the Wooldridge (2011) one step GMM version of OP and LP. I briefly present the three cases and I refer to Wooldridge (2011) and Akerberg, Caves, and Frazier (2006) for more details. In the empirical part of the analysis, I verify the robustness of the parameters of interest by considering the modifications suggested below.

4.2.1. Static Input Control

The static input control approach described above can, in principle identify the labor coefficient in a first stage, while identifying the other parameters in a second stage. Before laying out a more general identification strategy, where

essentially all parameters are estimated jointly using moments on the productivity shock, I briefly discuss what data generating process (DGP) could provide identification in the approach under Section 4.1. There is a separate literature on the ability to identify variable inputs in a OP-LP setting. However, in my setting the demand variation across firms is brought to the forefront, highlighting that it is hard to come up with a suitable DGP where labor can move around independently from all other inputs of production and all demand variables of the model captured by $\phi_t(m, k, q_{st}, qr, D)$. Without going into great detail, a DGP that delivers identification is one where firms make material choices, followed by labor choice, but both are made within the period $t - 1, t$ and add an optimization error to labor but none to materials. This would create variation in labor choices that is related to the variance in output conditional on the nonparametric function in (m, k, q_{st}, qr, D) .²⁰

I can relax this strong identification requirement by simply not identifying the labor coefficient in a first stage. Instead I identify it together with the other parameters by forming a moment on the productivity shock. When relying on materials to proxy for productivity, I collect all inputs in $\phi_t(\cdot)$ in a first stage:

$$\tilde{r}_{it} = \phi_t(k_{it}, l_{it}, m_{it}, q_{st}, qr_{it}, D) + \varepsilon_{it}.$$

From the first stage, I have an expression for productivity given all parameters and I can rely on the same moments to identify the production function coefficients, where the extra moment on labor, $E(v_{it+1}l_{it}) = 0$, provides identification. The only difference with the approach outlined before is that the labor coefficient is identified in a second stage.

4.2.2. Dynamic Input Control

The investment approach can, in principle, identify the variable input coefficients in a first stage. However, as under the static input model, we need a DGP which allows both labor and material choices to move around independently from the control function $\phi_t(i_{it}, k_{it}, qr_{it}, D)$. In this setting, variation in l_{it} and m_{it} can be obtained through an additional timing assumption of when exactly the productivity shocks hit the firm. Let variable inputs be chosen after the firm observes its productivity shock ω_{it-b} , where $b < 0$. Furthermore, an additional productivity shock occurs between $t - b$ and t . The latter creates variation in variable input choices conditional on the proxy for productivity $\phi_t(\cdot)$. The intuition behind this result comes from the idea that labor (material) is chosen

²⁰It is instructive to derive optimal material demand given my explicit demand and production structure, and to plug in the inverse material equation in the revenue production function. This highlights the identification issue in the first stage. In fact, if I were to directly observe output, $\alpha_l l_{it}$ would cancel out and illustrate the nonidentification result. However, the use of revenue data introduces additional variation but it does not help identification much since all relevant demand variation is controlled for through the productivity proxy $\phi_t(\cdot)$.

at $t - b$ without perfect information about what productivity at t is, and this incomplete information is what moves labor (material) around independently of the nonparametric function, where investment was set at $t - 1$ as it is a dynamic input decision.

To relax the extra timing assumption to obtain identification, I follow the same approach as under the static input control. I collect all production function inputs in $\phi_t(\cdot)$ in addition to investment (the proxy), the product dummies, and quota protection:

$$\tilde{r}_{it} = \beta_s q_{st} + \phi_t(i_{it}, k_{it}, l_{it}, m_{it}, qr_{it}, D) + \varepsilon_{it}.$$

From the first stage, I have an expression for productivity given parameters, and I can proceed as before and obtain estimates of the labor and material coefficient from $E(v_{it+1}l_{it}) = 0$ and $E(v_{it+1}m_{it}) = 0$, respectively. The second stage provides estimates of the variable input coefficients by noting that none of the lagged input choices should be correlated with the innovation in the productivity process, while lagged inputs are correlated with current inputs through serially correlated input prices, therefore qualifying them as instruments.

Both the static and dynamic input approaches can therefore be adjusted to accommodate a recent debate on the identification concerns in proxy estimators, as nicely summarized by Wooldridge (2011). However, the identification of a perfectly variable input, such as materials in my setting, is still not guaranteed as discussed by Bond and Soderbom (2005). I deal with this concern by considering a value added production function and imposing a fixed proportion technology on the production function whereby I eliminate the need to estimate the material coefficient. I present this robustness check in Section 6.

4.2.3. *Alternative Approach*

Wooldridge (2011) proposed an alternative implementation that deals with the identification of the production function coefficients and is robust to the criticism of Akerberg, Caves, and Frazier (2006). The approach relies on a joint estimation of a system of two equations using GMM, by specifying different instruments for both equations. I consider the Wooldridge approach while relying on materials m_{it} to proxy for productivity which the literature refers to as the Wooldridge–LP approach, and I briefly discuss some important features that apply in my setting.

Wooldridge considers moments on the joint error term $E((\varepsilon_{it} + v_{it})|I_{it}) = 0$, where I_{it} is the information set of firm i at t . Applying the Wooldridge approach to my setting implies having moment conditions on both idiosyncratic production and demand shocks, ε_{it} , and the productivity shocks, v_{it} . However, because of the joint estimation of both stages, this procedure requires estimation of all polynomial coefficients that approximate $h_t(\cdot)$, $g_t(\cdot)$, $\beta_{h,t}$, and $\beta_{g,t}$,

together with all production and demand coefficients, including the large number of product dummies. The sample analogue of these moments generates estimates for $(\beta_l, \beta_m, \beta_k, \beta_s, \delta, \tau)$ in addition to the polynomial coefficients on the functions $h_t(\cdot)$ and $g(\cdot)$.

The advantage of this approach is that bootstrapping is not required to obtain standard errors on the production function coefficients, and it produces more efficient estimators by using cross-equation correlations. However, this comes at the cost of searching over a larger parameter space, since I have to search jointly over the production function coefficients, the demand coefficients, and all polynomial coefficients used to approximate the functions $h_t(\cdot)$ and $g(\cdot)$. The alternative approach I rely on requires searching over fewer parameters. In addition, I can control for the importance of product effects outside the GMM procedure using my approach, which is important given the high dimension of the product dummy parameters. Furthermore, since all demand variables enter the proxy for productivity, $h_t(\cdot)$, and the quota protection variable enters the productivity evolution $g(\cdot)$, I further increase the dimension of the parameter space. These concerns are not present in the standard production function case where one either assumes observing quantities or directly observes it in the data.²¹

4.3. Productivity Estimates

I compute productivity $\hat{\omega}_{it}$ using the estimated parameters and plug them in

$$(24) \quad \hat{\omega}_{it} = (\tilde{r}_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_s q_{st} - \hat{\tau} q_{rit}) \left(\frac{\hat{\eta}_s}{\hat{\eta}_s + 1} \right).$$

where I rescale by the relevant markup as indicated by the difference between ω_{it} and ω_{it}^* throughout the text. Note that I do not subtract the product and group effects, since they become unimportant when I analyze the impact of protection on productivity changes because time invariant factors are eliminated. For the cross-sectional analysis, I can consider the productivity measure both with and without the product and product-group effects, and evaluate the role of the product and group dummies.²² The same is true for the role of the number of products when considering multiproduct producers.

I could directly rely on the second stage of my algorithm to compute productivity. However, to be able to compare my results across various proxy estimators, I could only rely on those observations with positive investment and I would lose at least 1 year of data since differences in capital stock are used to

²¹However, the Wooldridge-LP estimator can be easily implemented using publicly available STATA code (ivreg2). I estimate this on my data as a robustness check, while ignoring the product dummies.

²²For multisegment producers, the segment demand variable is expanded to $\sum s_{is} \hat{\beta}_s q_{st}$ and the markup term is a share weighted average across segments.

construct the investment data (which is standard). Moreover, omitting plants with zero investment would imply omitting the relatively lower productivity firms which are important to include to verify the relationship between reduced quota protection and productivity; that is, those might be the firms with an initially high level of quota protection where we want to verify the productivity impact of reducing protection. Olley and Pakes (1996) followed the same procedure in their study of productivity dynamics in the telecommunications industry.

The only difference between the productivity estimates that come directly out of the estimation procedure and those out of equation (24) is the role of measurement error and idiosyncratic shocks (u_{it}). The variance of my productivity estimates then contains the variance of the i.i.d. production and demand shocks, whereas the productivity estimates obtained inside the algorithm are by construction purged from these shocks in the first stage. The averages of both productivity measures are in fact identical. The only concern is therefore that I use a less precise measure of productivity. If my parameters are correctly estimated, then $\widehat{\omega}_{it} = \omega_{it} + u_{it}$ and, therefore, u_{it} should not be correlated with qr_{it} . I rely on (24) to obtain estimates for productivity and check whether my results are robust to using this alternative measure.

My approach generates productivity estimates purged from price effects while relying on the correct returns to scale parameter. I exploit the time series variation in production and demand to estimate the demand parameters, and by giving up the ability to estimate a change in the slope of the demand curve, I can estimate the slope for various product segments. However, this restriction does buy me more flexibility on the production function by allowing for dynamic inputs and additional state variables of the underlying firm's problem. It is useful to compare my productivity estimates directly to the standard sales per input measures for productivity. Let me collect all inputs into \mathbf{x}_{it} and the corresponding coefficients into β . In my notation, those standard estimates for productivity are obtained as

$$(25) \quad \widehat{\omega}_{it}^{st} = \widetilde{r}_{it} - \mathbf{x}_{it}\widehat{\beta}.$$

Note that price variation that is correlated with input variation is not part of the productivity measure: that correlation leads to biased coefficients of the production function and therefore leads to incorrect productivity estimates. Relying on my methodology delivers estimates for productivity corrected from price variation since they are based on the correct input coefficients by accounting for both simultaneity and price bias; they are given by

$$(26) \quad \widehat{\omega}_{it} = q_{it} - \mathbf{x}_{it}\widehat{\alpha}.$$

It is helpful to consider the difference between the standard sales per input measure and my corrected estimate,

$$(27) \quad \widehat{\omega}_{it}^{st} - \widehat{\omega}_{it} = (p_{it} - p_t) + \mathbf{x}_{it}(\widehat{\alpha}/|\widehat{\eta}_s|),$$

where I use the notion that $\beta = \alpha(\frac{\eta_s+1}{\eta_s})$. This expression shows that my approach purges the standard measures for productivity from price variation (uncorrelated with input variation) through the CES structure (through the terms $\beta_s q_{st}$ and ξ_{it}), and corrects for the appropriate returns to scale in production by correctly weighting the input variation by the correct input coefficients.

4.4. *Some Identification Issues*

The identification strategy of the structural parameters is very similar to that in Klette and Griliches (1996). However, there are two important differences. First of all, I control for unobserved productivity shocks by relying on a proxy for productivity. Second, I incorporate the product mix of a firm so that my identification strategy allows for a richer demand structure. More specifically, as I project firm-specific revenue on segment-specific output (which are weighted by the share of products in a given segment), product-group fixed effects, and firm-level protection rates, I control for unobserved prices and identify the parameters of both the production function and the demand system.

A crucial assumption throughout my identification strategy is that the product mix does not react to changes in protection and is time invariant. This condition is the result of a data constraint, that is, I only observe the product mix information for a cross section. However, given this limitation, I fully exploit this information and use it to put more structure on the demand system. This assumption seems to contradict recent evidence by Bernard, Redding, and Schott (2010) on product switching in U.S. manufacturing plants. However, my panel is 9 years, and the scope for adding and dropping products is therefore smaller. In further support of this assumption, I do observe the product mix over time for a set of firms in the Knitwear subsegment (see Table A.I). I see very little adjustment in the number of products over time and there is almost no adjustment in the number of segments in which a firm is active. In fact, year to year only 5 percent of the firms adjust their product mix and about 15 percent adjust over a 5 year horizon.²³

Whenever the fixed product mix assumption does not hold, it can potentially impact the ability to identify the production and demand parameters. Conditional on the input proportionality assumption, it only introduces deviation around the observed number of products over time in the error term ($np_{it} - np_i$). However, my framework incorporates the firm-level protection rate qr_{it} , and this controls for changes in the product mix that are correlated with changes in protection. Therefore, I can identify the coefficients as long as changes in the product mix are picked up by changes in trade protection. When relying on the dynamic control to proxy for productivity, it additionally affects the exact conditions for invertibility in the Olley and Pakes (1996) framework

²³Relying on this small sample, I could not find a strong relationship between labor productivity and the change in product mix.

and requires modeling the product mix choice as well. I refer to Das, Roberts, and Tybout (2007) where a dynamic model with two controls is introduced with an application to international trade.

If the product line changes over time, my estimates of productivity pick up changes in the product mix. Therefore, when projecting the productivity estimates on the change in protection, those coefficients capture changes in the product mix due to a change in protection. As a consequence, the results presented in this paper are consistent with the work of Bernard, Redding, and Schott (2011), who showed that firm-level productivity can increase after trade liberalization because firms adjust the product mix accordingly. Given the data constraint, I cannot further separate the pure productivity effect from this product reallocation and selection dimension. My approach still provides consistent estimates of the demand and production structure, and could potentially decompose the productivity effect into an intensive (change in productivity, holding number of products fixed) and an extensive margin (change in number of products, holding productivity fixed). However, the focus of my paper is on correctly estimating the impact of trade liberalization on firm-level productivity while controlling for unobserved prices; therefore, my results can be interpreted through the lens of product mix adjustment.

Finally, it is worth mentioning that if my assumption on $\tilde{\xi}_{it}$ fails and captures persistent demand shocks, I can accommodate for persistent demand shocks by simply collapsing the unobserved demand shock $\tilde{\xi}_{it}$ with unobserved productivity ω_{it} into a new state variable $\tilde{\omega}_{it}$. The same control function $h_i(\cdot)$ is now used *as long as* the unobserved demand shock $\tilde{\xi}_{it}$ follows the exact same Markov process as productivity.²⁴ This would imply that $\tilde{\xi}_{it}$ no longer enters in any of the expressions since it would be part of $\phi_i(\cdot)$. However, it would change the interpretation of the productivity estimates since they would contain those demand shocks ($\tilde{\xi}_{it}$). Levinsohn and Melitz (2006) explicitly assumed that a control function in materials and capital is sufficient to control for both unobserved productivity and all demand shocks to identify the coefficients of the production function and the elasticity of substitution. In contrast, I allow for unobserved demand shocks to be correlated with segment-level output and the various inputs. Note that in my estimation algorithm, described above, I rely on three different (observed) demand shifters (at the product, group, and firm level) and I verify the importance of this control by comparing my estimates of β_s to those where only the proxy for productivity is included.

²⁴In the case where $\tilde{\xi}_{it}$ captures serially correlated demand shocks but follows a different process over time, the investment proxy approach is directly affected by introducing an additional serially correlated unobserved state variable in the model, and this affects both the invertibility conditions and the ability to identify the parameters.

5. RESULTS

In this section, I compare the coefficients of my augmented production function to a few benchmark estimators. I demonstrate the importance of controlling for both unobserved demand and productivity shocks so as to recover direct estimates of segment-specific elasticities.²⁵ I recover estimates for firm productivity and relate them to the drastic change in trade protection in the textile market. In addition, I discuss the inability of the current available approaches to single out the productivity response from decreased trade protection.

5.1. *Production Function Coefficients and Demand Parameters*²⁶

In this section, I show how the estimated coefficients of a revenue production function are reduced form parameters of a demand and supply structure. As a consequence, the actual production function coefficients and the resulting returns to scale parameter are underestimated.

I compare my results with a few baseline specifications in Table VI: a simple ordinary least squares (OLS) estimation [1] and the Klette and Griliches (1996) specification in differences KG [2]. Furthermore, I compare my results with the Olley and Pakes (1996) and Levinsohn and Petrin (2003) estimation techniques to correct for the simultaneity bias [3]. I first compare the various benchmark coefficients to a highly aggregated version of my empirical model [4], where I only consider one demand parameter to characterize the textile industry. This model is similar to that used by Levinsohn and Melitz (2006), and this specification is useful to illustrate the importance of controlling for unobserved price variation around the aggregate producer price index.

Going from specification [1] to [2] illustrates that OLS produces reduced form parameters from a demand and a supply structure. As expected, the omitted price variable biases the estimates on the inputs downward and hence underestimates the returns to scale elasticity. Specification [2] takes care of unobserved heterogeneity by taking a first difference of the production function, as in the original Klette and Griliches (1996) paper. The coefficient on capital goes to zero as expected for a fixed input. In specification [3], the impact

²⁵With the additional assumption that firms are cost minimizing and do not face adjustment cost, one can, in principle, obtain estimates of markups from the production function coefficients; see De Loecker and Warzynski (2010). In this paper I am concerned with obtaining the correct productivity estimates.

²⁶All the results reported here are robust with respect to estimating the variable input coefficients (labor and materials) either using the GMM approach of Wooldridge (2011) or the second stage approach as described in Section 4. I thank Amil Petrin for making the LP-Wooldridge code available. Interestingly, the coefficients on the freely chosen variables are very stable across methods. The returns to scale parameter differs slightly but is not statistically different due to different capital coefficients. This shows that my correction for unobserved prices is robust to the use of a specific proxy estimator.

TABLE VI
PRODUCTION FUNCTION ESTIMATES^a

Coefficient on	[1] OLS	[2] KG		[3] Proxy	[4] Augmented		[5]: Single Segment
	β	β	α	β	β	α	β
Labor	0.230 (0.009)	0.245 (0.0120)	0.334 (0.034)	0.211 (0.011)	0.213 (0.011)	0.308 (0.062)	0.230 (0.017)
Materials	0.630 (0.007)	0.596 (0.013)	0.812 (0.052)	0.628 (0.009)	0.627 (0.008)	0.906 (0.175)	0.650 (0.013)
Capital	0.088 (0.007)	0.019 (0.011)	0.026 (0.014)	0.093 (0.008)	0.104 (0.006)	0.150 (0.034)	0.090 (0.006)
Output		0.266 (0.046)			0.309 (0.134)		0.260 (0.137)
η			-3.76			-3.24	-3.85
No. of obs	1,291	1,291		985/1,291	985		735

^aBootstrapped standard errors are given in parentheses. Results under [3] Proxy are obtained using the intermediate inputs as a proxy as suggested by Levinsohn and Petrin (2003) and are compared with the Olley and Pakes (1996) approach. The LP estimator was implemented using their estimator in STATA (levpet) and the Wooldridge (2011) version of LP using ivreg2 in STATA.

of correcting for the simultaneity bias changes my coefficients in the direction predicted by theory, that is, the labor coefficient is estimated somewhat lower and the capital coefficient is estimated higher. The omitted price variable bias is not addressed in the OP and LP framework as they are only interested in a sales per input productivity measure.²⁷ Both biases are addressed in specification [4], and the corrections for the simultaneity and omitted price variable go in opposite directions, therefore making it hard to sign the total bias a priori.

As expected, the estimate on the capital coefficient does not change much when introducing the demand shifter since the capital stock at t is predetermined by investments at $t - 1$; however, it is considerably higher than in the Klette and Griliches (1996) approach. The correct estimate of the scale elasticity ($\alpha_l + \alpha_m + \alpha_k$) is of the most concern in the latter and indeed when correcting for the price variation, the estimated scale elasticity goes from 0.9477 in the OLS specification to 1.1709 in the KG specification. The latter specification does not control for the simultaneity bias, which results in an upward bias on the variable inputs labor and material. This is exactly what I find in specification [4], that is, when correcting for unobserved productivity shocks, the implied coefficient on labor drops from 0.334 to 0.308 for the labor coefficient.

²⁷A downside is that the product-level information (number of products produced, segments, and which products) is time invariant and leaves me with a panel of firms active until the product information was available. Therefore I check whether my results are sensitive to this by considering a full unbalanced data set where I control for the selection bias (exit before 2000) as well as suggested in Olley and Pakes (1996). I can do this as the BELFIRST data set provides me with the entire population of textile producers. The results turn out to be very similar.

The estimated coefficient on the industry output variable is a direct estimate of the Lerner index and I also report the implied elasticity of demand. In Appendix B, I discuss in detail how the segment-specific shifters q_{st} are constructed using a firm's product mix. Moving across the various specifications, the estimate of the Lerner index (or the markup) increases as I control for unobserved firm productivity shocks.²⁸ The implied demand elasticities are around -3 . These estimates are worth discussing for several reasons. First of all, they provide me with a check on the economic relevance of the demand model I assumed. Second, they can be compared to other methods that estimate markups using firm-level production data.²⁹ It is because of the specific demand system that I obtain direct estimates of the markup on the total output variable. This is in contrast to the approach due to Hall (1988) where, in addition to standard cost minimization, we require that firms face no adjustment costs so as to estimate markups directly from the production function coefficients.

The last column of Table VI presents the estimates of the augmented production function for firms active in a single segment, specification [5]. As discussed in Section 2.2, I require an extra assumption on how inputs are allocated across segments and products so as to estimate my model on multi-segment producers. The estimates indicate that my results are not sensitive to this. For the remainder of the paper, I consider all firms in my data unless explicitly mentioned.

In Table VII I demonstrate the importance of controlling for unobserved demand shocks by estimating the full model as described in Section 4. I rely on product and product-group fixed effects and firm-specific protection measures to control for ξ_{it} in the augmented production function. As expected, I find significantly more elastic demand, confirming that demand is higher for firms active in relatively more protected segments, and thereby inducing a positive correlation between the segment demand variables (q_{st}) and the error term, containing variation in protection (qr_{it}). It is useful to refer back to Figure 1, where the difference in the rate of protection across segments and time is highlighted. In addition to the protection measure, my model controls for unobserved differences in demand conditions such as (average over the sample period) differences in demand for products and product groups, reflecting

²⁸The industry output variable captures variation over time of total deflated revenue and as Klette and Griliches (1996) mention, therefore potentially picks up industry productivity growth and changes in factor utilization. If all firms had a shift upward in their production frontier, the industry output would pick up this effect and attribute it to a shift in demand and lead to an over-estimation of the scale elasticity. In my preferred empirical model, I consider different demand elasticities at the segment level and can allow for aggregate (across all segments) productivity shocks.

²⁹In particular, Konings, Van Cayseele, and Warzynski (2001) used the Hall method and found a Lerner index of 0.26 for the Belgian textile industry, which is well within the range of my estimates.

TABLE VII
SEGMENT-SPECIFIC DEMAND PARAMETERS AND RETURNS TO SCALE^a

Demand Controls	Estimated Coefficient (β_s)		Implied Elasticity (η_s)	
	Not Included	Included	Not Included	Included
Industry (I)	0.35	0.26	-2.86	-3.85
Interior ($s = 1$)	0.24	0.16	-4.17	-6.25
Clothing ($s = 2$)	0.35	0.23	-2.86	-4.35
Technical ($s = 3$)	0.31	0.21	-3.23	-4.76
Finishing ($s = 4$)	0.33	0.22	-3.03	-4.55
Spinning ($s = 5$)	0.26	0.18	-3.85	-5.56
RTS	1.3	1.11		

^aDemand controls are product, product-group, and protection rate variables, (ξ_j , ξ_g , qr_{it}). All coefficients are significant at the 1 percent level.

consumer taste. It is interesting to note that the coefficients on the segment output variables are estimated more precisely when I control for unobserved productivity using the control function. Including the demand side controls has little impact on the estimated reduced form coefficients (β_l , β_m , and β_k) of the production function, but they obviously matter for the correct marginal product estimates (α_l , α_m , α_k) which require the estimates on the segment demand elasticities (η_s).³⁰

The results in Table VII demonstrate that controlling for the differences in protection rates across segments and over time is crucial to recover reliable measures for segment-specific elasticities and hence productivity. The fact that the coefficients become much smaller implies higher (in magnitude) elasticities of demand after controlling for unobserved demand shocks. This is a standard finding in the empirical demand literature. For example, for the Interior segment, the estimated demand elasticity goes from -4.17 to -6.25 after I control for unobserved demand shocks, implying a positive correlation between demand for products in a given segment and the rate of protection as measured by qr_{it} .

Given the functional form for demand and supply, these lower markup estimates have a direct impact on my estimates for returns to scale. I find significantly increasing returns to scale in production with a coefficient of 1.11. This is in itself an important result and supports the results of Klette and Griliches (1996), who discussed the downward bias of the production function coefficients due to unobserved prices.

³⁰I do not list the estimated coefficients of the production function again, as they hardly change compared to the results in the last column of Table VI. The coefficients on labor, materials, and capital are obtained by multiplying the reduced form estimates by the segment-specific inverse markup estimate.

In sum, my results indicate that both the omitted price variable and the simultaneity bias are important to correct for, although the latter is somewhat smaller in my sample. The estimated reduced form parameters (β) do not change much when controlling for the omitted price variable, after correcting for the simultaneity bias. However, it has a big impact on the estimated production function parameters (α), which by itself is important if one is interested in obtaining the correct marginal products. Finally, the estimated coefficients of the production function and the demand elasticities, and hence productivity, are not sensitive to the specific proxy estimator approach (OP, LP, and modifications discussed in Section 4). The various proxy approaches produce very similar coefficients of the reduced production function coefficients (β) and do not impact the demand parameters. In Section 6, I discuss two additional robustness checks. The different approaches do, however, imply different modeling assumptions as discussed in detail in Section 4 and, therefore, show that my results are robust to them.

5.2. *Estimating the Effect of Trade Liberalization on Productivity*

I rely on my estimates of productivity to estimate the firm-level productivity reaction to relaxing quota protection in the EU textile market. As discussed in Section 4, my estimation procedure provides a direct nonparametric estimate of the effect of quota on productivity. Once I have all the model's parameters estimated, I can compute productivity and therefore obtain an estimate of $g(\cdot)$ which describes how past productivity and quota affect current productivity. Before presenting my results, I briefly discuss the main approach in the current literature and contrast it to my setting.

5.2.1. *Standard Approach*

Attempts to identify the productivity effects from trade liberalization in the literature can be classified into two main approaches: a two-stage and a single equation approach. Based on my empirical framework, I briefly discuss how neither approach is able to single out productivity responses to the reduced quota protection or, in general, to any change in the operating environment of firms that impact demand for the goods marketed.

The Two-Stage Approach. In this approach, the strategy follows two steps, where the first is estimating the production function while ignoring the unobserved price problem. The second stage then simply projects the recovered "productivity" estimate ω_{it}^{st} against the shift in trade regime. It is clear that this approach does not allow the productivity response to be isolated from the demand response since the productivity estimates capture price and demand variation. This approach typically considers a variant of the regression

$$(28) \quad \omega_{it}^{st} = c + \lambda q r_{it} + e_{it},$$

where the interest lies in estimating λ . Equation 28 shows the very strong assumptions one needs to invoke to be able to identify the productivity impact from decreased quota protection: protection cannot impact prices—except through productivity—and cannot be related to returns to scale in production. Using the expression derived in (27), this two-stage approach then implies correlating the entire term $(\omega_{it} + p_{it} - p_t + \mathbf{x}_{it}(\alpha/|\eta|))$ to quota protection and leads to incorrect estimates of the quota effect. In addition, this approach does not allow protection to impact the evolution of productivity when estimating the production function itself, which is at odds with the research question.

The Single Equation Approach. This procedure starts out with specifying a parametric function for productivity in the variable of interest, here trade liberalization (qr_{it}). For example, let me consider a simple linear relationship $\omega_{it} = \lambda qr_{it} + e_{it}$, where distributional assumptions are made on e_{it} . Substituting this expression for productivity into the production function generates an estimating equation

$$(29) \quad \tilde{r}_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \lambda qr_{it} + e_{it}^*,$$

where λ is meant to capture the productivity effect of a reduction in protection, and where e_{it}^* now includes e_{it} and unobserved prices. The coefficient λ is not identified unless the protection rate variable, qr_{it} , is not allowed to be correlated with (unobserved) prices.

Both the single equation and the two-stage approach are expected to lead to an incorrect estimate of the impact of trade liberalization on productivity. In fact, the single and two-stage approaches should provide identical results on the estimate for λ . However, the two-stage approach has the potential to produce productivity estimates that are obtained while correcting for the simultaneity bias using the standard OP–LP approach. I compare my estimates to the two main approaches in the literature. Putting all the different approaches side by side allows me to shed light on the importance of controlling for unobserved productivity shocks, as well as controlling for unobserved prices in obtaining the correct estimated protection effect on productivity. My approach relaxes the strong assumption needed for both approaches—that changes in quota protection do not affect prices and firm-level demand—while controlling for unobserved productivity shocks. The ability to separately identify the demand from the productivity effect comes from the notion that prices reflect differences in residual demand and hence differences in quota protection, whereas the supply effect comes through productivity which takes time to materialize. This identification strategy implies that we expect to see separate roles for the contemporaneous and the lagged quota variables in a simple OLS regression of the production function while ignoring the simultaneity and omitted price variable bias. When running such a regression on my data, I obtain a strong effect on the contemporaneous quota variable, while the coefficient on

the lagged quota variable is smaller in magnitude and not significant. The next section produces the structural estimates while controlling explicitly for both unobserved productivity and unobserved prices as outlined in Section 4.

5.2.2. *Controlling for Price and Demand Effects*

To verify the extent to which trade liberalization, measured by a decrease in quota restrictions, has impacted the efficiency of textile producers, I compare my results to several different specifications. I start out with following the standard practice in the literature, and consider both a single equation approach and a two-stage approach, as discussed above, which both ignore unobserved prices and productivity. In particular, the single-stage approach estimate of λ is obtained after running the regression (29) using OLS (Approach I).³¹ I then proceed by considering a two-stage approach (28) where I rely on the standard OP-LP productivity estimates (Approach II).³² The final benchmark model is a two-stage approach which relies on productivity estimates from an adjusted OP-LP framework where quota protection enters the model through the process of productivity, $\omega_{it} = g(\omega_{it-1}, qr_{it-1}) + v_{it}$, and hence in the control function (Approach III). This benchmark model, Approach III, generates nonparametric estimates of the productivity effect of quotas through the estimate of $g(\cdot)$. I report the average to compare with the other models and, in addition, list the support of the estimated effect. It is important to note that the first two benchmark results are not directly comparable to my results as they report the level effect of quotas and productivity, whereas I am concerned with obtaining the correct estimates of within firm productivity changes. Benchmark III, however, is directly comparable.

Table VIII presents the results of the various estimates, where it is important to note that the sign of λ is expected to be negative if trade liberalization effects productivity at all, since $qr_{it} = 1$ under full protection and is 0 if not a single product-supplier combination faces a quota. The first row presents the results from a simple OLS regression of deflated revenue on the protection variable, controlling for input use. The coefficient is highly significant and negative, suggesting about 16 percent higher productivity from eliminating all quotas on all products. As discussed before, this regression cannot separate the impact of protection on demand (and hence prices) and productivity. In addition, it considers quotas that directly impact the level of productivity, and would suggest a very high effect when ignoring price and demand effects. Approach II.1 shows the very small impact on the estimate of λ by relying on productivity estimates obtained from a OP-LP approach, which corrects for unobserved productivity shocks. Both Approaches I and II are not directly comparable to my estimates,

³¹The two-stage approach without any correction for the unobserved productivity shocks produces the same estimate for λ , but differs in precision.

³²These estimates rely on an exogenous Markov process for productivity and control for unobserved productivity shocks using either material demand or investment, in addition to capital.

TABLE VIII
IMPACT OF TRADE LIBERALIZATION ON PRODUCTIVITY^a

Approach	Description	Estimate	Support
I	OLS levels	−0.161* (0.021)	n.a.
II.1	Standard proxy-levels	−0.153* (0.021)	n.a.
II.2	Standard proxy-LD	−0.135* (0.030)	n.a.
III	Adjusted proxy	−0.086 (0.006)	[−0.129, −0.047]
IV	Corrected	−0.021 sd: 0.067	[−0.27, 0.100]
V	Corrected LD	−0.046** (0.027)	n.a.

^aI report standard errors in parentheses for the regressions, while I report the standard deviation (sd) of the estimated nonparametric productivity effect in my empirical model (given by $g(\cdot)$). * and ** denote significant at 5 or lower and 10 percent, respectively. LD refers to a 3 year differencing of a two-stage approach where Approach II.2 relies on standard productivity measures, as opposed to Approach V, which relies on my corrected estimates of productivity.

as suggested before. I therefore consider an adjusted proxy estimator where I nonparametrically estimate the lagged quota effect relying on my productivity process while still ignoring unobserved prices. The productivity effects now reflect productivity changes and how these within firm productivity changes are related to trade protection. The average effect of quotas on productivity is reduced to −0.086. The support of the estimated effect indicates that eliminating quotas impacts productivity positively throughout the distribution.

Moving to the results from my approach, Approach IV, where unobserved productivity and prices are jointly controlled for, I find a substantially lower average quota effect of −0.021. This results indicates that eliminating quotas on all products would, on average, only raise productivity about 2 percent, as opposed to almost 9 percent when ignoring the price effect. Just as in Approach III, I obtain a nonparametric estimate of the productivity effect, and the support suggests a wide range of outcomes, with a large mass around zero. Interestingly, my estimates of $g(\cdot)$ also indicate that the productivity effect of quotas is positive for relatively low productivity firms, albeit still much lower in magnitude. The latter comes from the estimated coefficients of $g(\cdot)$, β_g , that capture the interaction between quota protection and productivity.

A final set of results is presented under Approaches II.2 and V, where I compare a simple long difference version of (28) while relying on standard productivity estimates and my corrected estimates, respectively. My results imply that abolishing all quotas over a 3 year period would merely increase firm-level pro-

ductivity by 4.5 percent as opposed to 13.5 percent when relying on standard measures of productivity.

5.2.3. *Additional Results*

I briefly discuss a few other results that emerge from my analysis: the time aspect of the productivity effects, the potential separate role of enlarging quotas as opposed to abolishment, and implications for the effect of protection on prices charged.

As discussed in Section 3.1, a significant part of reduction in protection took place after the Europe Agreements were signed with various Central and Eastern European countries (CEECs). The sharp fall in the number of quotas in the period between 1994 and 1997 is consistent with the preparation process for EU enlargement toward Central and Eastern Europe (CEE). By the year 1998, almost all trade barriers between the EU and the candidate countries of CEE were abolished, which implied that industrial products from the associated countries (mostly CEE) had virtually free access to the EU with restrictions in only a few sectors, such as agriculture and textiles. Using my estimates, I find that, if anything, the productivity effects are not constant over time and are somewhat higher during the first half of the sample, although still relatively small in magnitude compared to relying on standard approaches.

Another channel through which EU trade policy relaxed quota restrictions was by increasing the level of existing quotas for a set of supplying countries. To verify the impact of this on productivity, I can only consider product categories where I observe a positive level of protection. Furthermore, I only consider quotas where the unit of measurement of a quota level is constant within a given industry code (23 categories). This dimension of opening up to trade has been for imports coming from outside CEE. Table A.IV lists the supplying countries where relaxing import restrictions mainly occurred through higher levels of quotas. I report the increase in the average level per quota during my sample period 1994–2002 and list the countries that gained access to the EU textile market. For instance, the average quota level on textile products from Pakistan has more than doubled over a 9 year period (129 and 144 percent, depending on product category). This process is not captured by the quota restriction variable that picks up whenever a quota on a given product from a supplying country is abolished. To verify the impact of increased quota levels, I simply correlated my estimate of productivity with a variable that measures the total level of quotas (in logs) while controlling for qr_{it} . The coefficient on the *level* variable is estimated with a positive sign, indicating that an increase in the level of quotas had a small but positive effect on productivity. The point estimate suggests an elasticity of 1.9 and implies, on average, a moderate effect of increasing quota levels on firm-level productivity.

Finally, in standard approaches, the coefficient on protection measures the effect of quota protection on revenues, including both the demand and the productivity effect. Using my structural model of demand and production, I can

back out estimates of firm-level prices, and I find that these are highly positively correlated with protection, suggesting that firms facing stronger competition on average charge lower prices.³³

5.3. *Collecting Results*

In sum, across all specifications, using standard measures for productivity leads to overestimating the productivity response to trade liberalization. These results indicate that correcting for unobserved price and demand effects leads to substantially lower productivity gains, ranging between one-third and one-fourth, and suggests that trade liberalization substantially impacts firm-level demand and hence prices. These observations then imply a very different interpretation of how opening up to trade impacts *individual* firms.³⁴

My results can be interpreted as a decomposition of *measured productivity gains* from relaxing trade protection into productivity effects and price–scale effects, and indicate that only a small share (ranging up to 20 percent) is associated with true productivity gains. The fact that after my correction, reduced quota protection still is associated with productivity gains, although small, is consistent with the work of Bernard, Redding, and Schott (2011), since my productivity estimates potentially capture product mix responses as discussed in Section 4.4. In the next section, I check whether my results are sensitive to relaxing some of the assumptions related to the production technology and the demand system.

6. ROBUSTNESS ANALYSIS

In this section, I verify whether my results are robust to the specific production function and demand system. Specifically, I test whether the demand elasticities are sensitive to a specific production function. On the demand side, I show that my approach is consistent with assuming a restricted version of a nested CES model of demand and I test the importance of this restriction.

6.1. *Relaxing Production Technology*³⁵

I verify whether my estimated demand parameters are sensitive to the specific choice of a production function. A more flexible approach allows for a

³³This result is obtained by first computing prices by using $p_{it} = \omega_{it}^{st} - \omega_{it} - x_{it}(\alpha/|\eta|) + p_t$ and then running a simple OLS of p_{it} on qr_{it} while controlling for unobserved firm-specific shocks.

³⁴However, average productivity of an industry can still increase due to the elimination of inefficient producers from the productivity distribution. In a different context, Syverson (2004) demonstrated the importance of demand shocks in increasing average productivity of producers through exit of inefficient producers.

³⁵All the results on the relationship between productivity and trade liberalization are robust to the use of productivity estimates under the various extensions and alternatives discussed in this section.

general production function where productivity shocks are additive in the log specification, $Q_{it} = F(L_{it}, M_{it}, K_{it}) \exp(\omega_{it} + u_{it})$, and thus allows for flexible substitution patterns among inputs such as the translog production function. However to recover the production function parameters, I have to specify moment conditions of the data on L_{it} , M_{it} , and K_{it} .

I consider the results in Section 5 (baseline) and compare them with estimates obtained from a more flexible approach, while relying on investment to proxy for productivity.³⁶ The first stage is then reduced to the regression

$$(30) \quad r_{it} = \sum_s \beta_s(s_{is}q_{st}) + \phi_t(l_{it}, m_{it}, k_{it}, i_{it}, qr_{it}, D) + \varepsilon_{it},$$

where I am only interested in the coefficients on the segment output variables. Table IX shows that the estimated demand parameters are well within the range of the less flexible model used in the main text. The estimates of the demand parameter at the industry and segment level are robust with respect to relaxing the assumptions on the production technology. For example, for the Interior segment, the estimated markup lies between 0.17 and 0.14.

I also check whether the estimated demand parameters are robust to the use of a value added production function whereby I allow for a fixed proportion of materials per unit of output in the production technology. The last row in

TABLE IX
ESTIMATED DEMAND PARAMETERS UNDER ALTERNATIVE SPECIFICATIONS^a

Specification	Segment					
	Industry	Interior	Clothing	Technical	Finishing	Spinning
Baseline	0.26	0.16	0.23	0.21	0.22	0.18
Flexible	0.22	0.14	0.23	0.19	0.22	0.21
Value added	0.29	0.20	0.21	0.27	0.25	0.21
Unrestricted	$\sigma = 0.008$ (0.113)	0.17	0.25	0.21	0.23	0.19

^aBaseline specification is compared to (i) Flexible, which allows for a general production function that is log additive in productivity, (ii) to a Value added production function specification, and (iii) to an unrestricted nested CES demand system. For the latter, I report the estimated cross-segment correlation coefficient σ and its standard error. I suppress the bootstrapped standard errors on the demand parameters, since they are all significant at the 1 percent level.

³⁶In addition, the flexible approach no longer takes a stand on whether labor and materials are static or dynamic inputs, and coincides with the approach discussed in Section 4.2. More importantly, it does not rely on a specific timing of the productivity shock and inputs to obtain consistent estimates of the demand elasticities. I do not change the properties of the segment output variables and still rely on them being not serially correlated conditional on all other demand variables in the model.

Table IX shows that the estimated demand parameters hardly change. In addition, the results presented in Section 5 are robust with respect to relying on productivity estimates from a value added production function. This robustness check deals directly with the observation of Bond and Soderbom (2005), who argued that it may be hard to identify coefficients on a perfectly variable input, such as materials in my case, in a Cobb–Douglas production function.

6.2. *Alternative Demand Systems*

I briefly show how my approach is equivalent to a discrete choice model often used in the empirical demand estimation literature. The parameters have slightly different interpretations, but all of the main results on the productivity response of liberalizing trade are unchanged. More precisely, I show that the empirical model I rely on in the main text can be generated from a logit or restricted nested CES or logit model of consumer choice. It is important to stress that the inability to measure prices and quantities directly limits the demand system I can rely on. An important feature of the demand system I suggest is the ability to relate log price to log quantity and observed demand shocks that vary over time and segments, which allows identification of the demand parameter by segment.

The discrete choice model consistent with my main empirical model has an indirect utility function V_{ljt} for consumer l buying good j at time t , consisting of a mean utility component and an idiosyncratic preference shock ζ_{ljt} , which is assumed to be drawn from a Type I extreme value distribution as in Berry, Levinsohn, and Pakes (1995). The mean utility component in my framework is simply a function of the logarithmic price p_{jt} , product fixed effects δ_j , and an unobserved demand shock ξ_{jt} .³⁷ This leads to the following specification for indirect utility:

$$(31) \quad V_{ljt} = \delta_j D_j + \eta p_{jt} + \xi_{jt} + \zeta_{ljt}.$$

The next step is to aggregate over individual choices to buy good j , and I recover a well known expression for the market share of good j relative to the outside good of the model,

$$(32) \quad \ln(ms_{jt}) - \ln(ms_{ot}) = \delta_j D_j + \eta p_{jt} + \xi_{jt}.$$

Starting from log market share and simply rearranging terms using that $\ln(ms_{jt}) = \ln Q_{jt} - \ln Q_{st}$, I obtain an expression for log price and plug it into

³⁷Introduction of the logarithmic price into the indirect utility function is the key difference between the (nested) CES and the (nested) logit model. Anderson, de Palma, and Thisse (1992) provided a good overview of the similarities of both models. To see this, it is useful to rewrite the CES demand system to make it directly comparable to the logit (i.e., $\ln(Q_{jt}/Q_{st}) = \eta(p_{jt} - p_t) + \xi_{jt}$).

the revenue expression to retrieve the same estimating equation,

$$(33) \quad r_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_s q_{st} + \delta_i D_i + \omega_{it}^* + \xi_{it}^* + u_{it},$$

where I consider single product producers for simplicity (i.e., $i = j$),³⁸ and where now $\beta_0 = \frac{1}{|\eta|} \ln(ms_o)$, $\beta_h = (\frac{\eta+1}{\eta})\alpha_h$ for $h = \{l, m, k\}$, and importantly $\beta_s = \frac{1}{|\eta|}$. It is important to note that total output enters in exactly the same way, leading to identification of η in the production function framework.

The difference between the CES model and the logit is clearly the interpretation of the estimated demand parameter η . In the CES case, the estimated coefficient β_s is a direct estimate of the Lerner index ($\frac{1}{|\eta|}$) or of the elasticity of demand (η). When relying on the logit demand structure, the estimated parameter η is used to compute own and cross-price elasticities. However, in this setup with log prices in the indirect utility function, they are identical (Anderson, de Palma, and Thisse (1992)).

It is well known that the logit model makes very strong assumptions about the substitution patterns across the various goods in the market, just like the CES demand structure. However, I allow for different substitution patterns across the various segments of the market. In this way, I am estimating a restricted version of a nested CES model, whereby the correlation of unobserved demand shocks across segments is assumed to be zero, after controlling for subsegment and product fixed effects.

Working through the same steps as above, I recover a similar estimating equation for a nested CES demand system where σ measures the correlation across segments. As Berry (1994) mentioned, we can interpret this model as a random coefficients model involving group-specific dummy variables. The advantage of the nested structure over the standard CES (or logit) is that I can allow for correlation of utility between groups of similar goods. This advantage comes at the cost of having to order the goods in a market in well defined nests. I rely on the classification presented in Table A.II to create segments and subsegments of the textile industry. It is important to note that relaxing the substitution patterns among the goods further reinforces the argued importance of controlling for unobserved prices and demand shocks. The ultimate constraint on modeling substitution patterns is the inability to observe quantities and prices for individual goods, which is a standard constraint in this literature.

Proceeding as before by rearranging terms to get an expression for p_{jt} , I obtain the same expression as before (i.e., (33)), with only an extra term that captures the share of segment s in total demand, $q_{s|It}$ (where subscript I denotes the textile industry), which provides information on σ .³⁹ The coefficient

³⁸I show this for a single product producer. For multiproduct firms, I need an additional step to aggregate to the firm level.

³⁹The reduced form parameters of the production function are now given by $\beta_h = (\frac{\eta_s+1-\sigma}{\eta_s})\alpha_h$ for $h = \{l, m, k\}$. I rely on the same demand controls to estimate both the segment-specific demand parameters and the additional parameter σ .

on this extra term is a direct estimate of the correlation across the various segments. The last row in Table IX reports the coefficients of an unrestricted nested CES demand system and I recover an insignificant estimate of 0.008 for the cross-segment correlation parameter σ . Therefore, in my particular application, I cannot reject the restricted version where the cross-segment correlation is set to zero. Given the different product categories listed in the various segments, this result is not surprising (see Table A.I).

I also considered the demand system one level lower in the structure of products, whereby I estimate a demand parameter for each subsegment (e.g., Mobiltech). However, this implies that more than 50 extra demand parameters need to be estimated in addition to the control function and the product dummies, and leads to a low testing power. I only find a few subsegments for which the markup is differently estimated.

In sum, my demand specification is consistent with a random utility discrete choice demand system. The results further support the specification relied on throughout the paper, where I allow for different parameters per segment. However, it is clear that my methodology does not rule out richer substitution patterns across products.

7. REMARKS AND CONCLUSION

In this section, I briefly discuss a few important implications that emerge from my findings. Detailed discussions of these implications are separate research questions on their own and are beyond the scope of this paper. This section is meant to highlight a few important avenues for research that directly follow from this paper. I conclude with an overview of my main results and findings.

7.1. *Remarks*

This paper shows the importance of correctly estimating the effect of trade policy on productivity. The suggested correction is also expected to be important for any reallocation analysis where researchers are interested in the covariance between productivity and the weight of an individual producer in the industry or economy at large. Regardless of the specific method used to aggregate productivity across individual producers, it is clear that relying on productivity measures that contain prices and demand shocks leads to an incorrect assessment of the underlying sources of aggregate productivity growth. I find a strong covariance of market share and my implied estimates of prices, controlling for the correct returns to scale, that suggests that revenue based productivity measures are not sufficient to measure the extent to which resources get reallocated across producers based on productivity differences. This helps me further evaluate how trade liberalization impacts the productivity of individual producers and that of industries as a whole. A full analysis of the reallocation

effects lies beyond the scope of this paper, and I refer to Petrin and Levinsohn (2010) for more details on the aggregation of producer-level productivity estimates.

Second, my estimates can directly shed light on whether traditional productivity measures are good measures of productivity. Using my estimates, I find a positive correlation between the standard measures of productivity and prices, whereas prices are negatively correlated with my corrected productivity estimates, as predicted by a large class of economic models in international trade and industrial organization. It is interesting to compare the correlation coefficients using my results with those of Foster, Haltiwanger, and Syverson (2008), who observed prices at the plant level for a subset of U.S. producers in the U.S. census data set. I obtain similar correlation coefficients without observing prices and quantities produced at the firm level. More precisely, I obtain a positive correlation of 0.12 between prices and standard revenue based productivity estimates, while prices and my corrected productivity estimates are negatively correlated (-0.35). Foster, Haltiwanger, and Syverson (2008) found correlation coefficients of 0.16 and -0.54 , respectively. My results therefore show that correcting for unobserved prices and demand effects is absolutely critical in obtaining measures for productivity.

7.2. Conclusion

I analyze productivity responses to a reduction in trade protection in the Belgian textile industry using a matched product–firm-level data set. By introducing demand shifters, I am able to decompose the traditional measured productivity gains into real productivity gains and price and demand effects. The empirical method sheds light on other parameters of interest, such as the price elasticity of demand, and my results highlight the importance of both productivity and price responses to a change in a trade regime.

Combining a production function and a demand system into one framework provides other interesting results and insights with respect to product mix and market power. I find that including the product mix of a firm is an important dimension to consider when analyzing productivity dynamics. Even if this has no impact on the aggregation of production across products, it allows estimation of different elasticities across product segments. In the context of the estimation of production functions, multiproduct firms have not received a lot of attention. The main reason for this is the lack of detailed product-level production data: input (labor, material, and capital) usage and output by product and firm. I observe the number of products produced per firm and where these products are located in product space (segments of the industry). This allows specifying a richer demand system while investigating the productivity response of trade liberalization, controlling for price and demand shocks.

While I find positive significant productivity gains from relaxing quota restrictions, the effects are estimated to be substantially lower, up to 20 per-

cent, compared to using standard productivity estimates. The latter still capture price and demand variation (across product segments and time) which are correlated with the change in trade policy, leading to an overestimation of productivity gains from opening up to trade. The suggested method and identification strategy are quite general and can be applied whenever it is important to distinguish between prices and physical productivity.

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